# Qi Macro Factor Equity Risk Model: Motivation, Methodology and Empirical Notes

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May 2025

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# 1. Introduction

## 1.1 Executive Summary

Factor investing has become widely popular across a broad swathe of investment strategies in the last three decades. The focus has been on fundamental factor models which were designed for equities and other linear instruments. Until now, macroeconomic factor models and macro effects were largely ignored as computational power and techniques had to catch up to statistical requirements. In this paper, we introduce Quant Insight's (Qi) cutting-edge macro factors as vital and unique tools in the efforts to identify, understand and control the macroeconomic risks whipsawing portfolios in the post COVID world.

A factor can be thought of as any characteristic relating to a group of stocks that is important in explaining their return and risk. Extensive academic research has shown the validity of the style factor approach, viz that certain factors, effectively intrinsic stock characteristics, have historically earned a long-term risk premium and represent exposure to systematic sources of risk. Common "equity risk premia" factors include Value, Low Size, Low Volatility, High Yield, Quality and Momentum.

Style Factors work over the long term but shorter term, the market is more and more driven by macroeconomic indicators that change at much shorter frequencies and drive prices. Qi gathers a broad range of macro factors and builds models that demonstrate their strong explanatory power over security prices. These factors include GDP growth, interest rates, FX, commodity prices, credit spreads, inflation rates and risk indicators.

Critically, Qi's macro factors are not intrinsic to stocks. They are "environmental" factors that may be dynamic and shift over time. A stock may begin the year being positively related to GDP growth but by the end of the year that relationship could have gradually changed to a negative sensitivity, reflecting a change in the prevailing market regime. The dynamic nature of these macro factor relationships, the inter-relatedness of macro factors themselves and the infrequent nature of data releases has stymied the development of solutions despite the dominance of macro in day-to-day market moves.

Qi presents a novel solution to control macro risk and improve portfolio risk adjusted returns. In this paper we will introduce Qi macro factors, discuss Qi's modelling method to attribute returns and risk to macro factors and showcase practical applications.

## 1.2 Motivations

It has long been successfully argued that stocks, in the long run, are driven by fundamentals which represent an intrinsic quality of the stock. This intrinsic quality is often associated with the microeconomic characteristics of the company – its relative competitiveness as a company in the business world. The quantification and modelling of microeconomics is constrained by the quarterly (at best) frequency of stock earnings updates, while stock prices move tick-to-tick through the day. Alternative data sources have tried to fill this gap with higher frequency data but thus far a compelling widely applicable model has not been forthcoming. Thus, we are presented with a significant challenge and opportunity -- understanding the shorter term moves in stocks.

It is broadly acknowledged throughout the history of markets that macro is often a significant source of short-term risk and return. However, macro is the among the least understood of equity drivers owing to its diversity, the interconnectedness of the various macro factors and general complexity. Furthermore, in the post-GFC world of low rates, outside of a company's microeconomic characteristics, macro effects were subdued while fundamental factors dominated risk.

An added layer of complexity, macro is also a dynamic driver that changes over time - it is not an intrinsic characteristic of a stock. Macro impacts tend to change over time => e.g. the S&P500 index is sometimes positively sensitive to economic growth, but sometimes it is the reverse. This type of behavior is outside the purview of traditional fundamental factor model construction, but it is very relevant to massive fluctuations in the market. Fed policy forecasts, real interest rates, and US GDP variability played a considerable role in moving the market 20-30% from 2022 to the time of writing of this paper. A priori, a company's intrinsic attributes to a macro factor are unknown – macro factor returns are available, but asset exposures must be solved for. This is in stark contrast to a traditional fundamental factor risk model where the challenge is in reverse – fundamental factor exposures are known but fundamental factor returns are solved for via a cross-sectional regression of the estimation universe.

Asset managers need to identify the macro drivers of financial markets and securities. The purpose of factor risk modelling is to reveal the anatomy of your portfolio. In so doing, reveal the implicit bets you don't have an edge in, and in turn, isolate and limit that exposure. Macro drivers encompass a range of factors, such as economic growth, monetary policy, impact of quantitative easing, risk aversion, credit spreads, commodity prices, and many more. Qi's macro factor framework drives insights in an intuitive, straightforward, and systematic manner. It enables asset managers to visualize financial data, identify patterns and make rigorously determined risk forecasts. This results in a better-informed trade selection and maximizes the value of the managers' view by identifying true portfolio exposures and risk effects. The Qi-Macro Factor Equity Risk Model (MFERM) provides a risk and return attribution framework to quantify the impact of macro and crucially help to answer if an asset manager is being compensated to take macro risk i.e. is macro providing a tailwind or headwind. The model can be viewed in isolation or used to complement or supplement a portfolio's risk analysis.

### 1.3 Fundamental Style Factors vs. Macro Factors

In general, a factor can be thought of as any characteristic relating to a group of securities that is important in explaining their returns and risk. As noted in the early CAPM-related literature, the market ("beta") can be viewed as the first and most important equity factor. Beyond the market factor, researchers generally look for factors that are persistent over time and have strong explanatory power over a broad range of stocks. There are three main categories of factors: macroeconomic, technical, and fundamental.

The most widely used factors today are fundamental and technical factors. Fundamental factors capture inherent stock characteristics such as Value, Growth, and Size while technical factors like Momentum and Mean Reversion capture behavior embedded in price history. These factors have been studied for decades as part of academic asset pricing literature and practitioner risk factor modelling research. Fama and French (1992, 1993) put forward a model explaining US equity market returns with three factors: the "market", the size factor (large vs. small capitalization stocks) and the value factor (low vs. high book to market). The momentum factor was added later, and further development continues ad infinitum (you can now have "Google Hits" as a factor).

However, stocks have other characteristics outside of fundamental and technical factors, particularly macro. These are outside the current focus of providers of fundamental factor models – a macro approach will need retooling of data, infrastructure, and expertise. Qi has the analysis of macro effects through innovative solutions using the latest data, technology, and mathematical techniques.

We find that a complete set of macroeconomic factors, encompassing the broad macroeconomic universe, can typically explain on average 34.6% (RSq) of the daily return of the S&P 500 universe of stocks. There is of course a distribution around these averages, with various stocks, sectors and indices being more macro driven than others at different times.

The models use daily returns to derive linear relationships for stocks based on a broad set of macroeconomic factors. Partial Least Squares Regression is used to develop the model and map their relationships with intuitive results. Over the long term a stock's fundamentals may well win out (e.g. superior earnings driven by innovation – an "alpha" factor). However, the shorter-term volatility (weeks and months) induced by macro is becoming more problematic for institutional investors. Like fundamental factor models, Qi macro models can be used at the portfolio level or asset level to decompose risk sensitivities – i.e. to identify, understand and control the macroeconomic exposures of portfolios.

## 2. Methodology

### 2.1 Fundamental Cross-Sectional Models vs. Qi Time Series Approach

It is important at this point to provide some color on the fundamental cross-sectional approach for modelling equity risk and the reasoning behind the choice of the Qi-timeseries approach to modelling macro risks embedded in equities.

Fundamental cross-sectional risk models are well-known and accepted in the industry today. The approach is based on first defining several descriptors that measure fundamental (Book-to-Price, Div-to-Price etc.) and technical (historical beta) characteristics of stocks. The descriptors have a 1x1 or n x1 relationship with the factors being included in the model and are combined using several empirical techniques to arrive at a numerical measure defining the factor (Value/Growth). These factors are then z-scored against an estimation universe to arrive at relative exposures for the equities. A cross-sectional regression is then used to produce an estimate of the factor returns. The factor returns and the covariance between those factor returns are then used to make risk forecasts and return attributions. These risk models provide an important way of analyzing the fundamental risks embedded in stocks which is the cornerstone of fundamental investing. In addition, the cross-sectional approach solves the problem of sparse historical data through the choice of a large estimation universe and access to point-in-time fundamental data.

As noted earlier, macro risks have been acknowledged to be significant drivers of short-term risk and return. However, macro risks are not an intrinsic (fundamental) characteristic of stocks. They are external factors yet exhibit a strong relationship to the performance and risk in equities investing. Macro impacts change over time and as such the relationship with equities is time-variant and regime-driven. Macro factors also exhibit high collinearity. Qi's innovative answer to this challenge is a solution that is both stable over time but also appropriately responsive to market conditions. It also deals with the essential collinearity that exists in the macro universe and with non-stationarity – the trending nature of many macro factors and indeed the stock market. Driving the next evolution of factor development, Qi's method yields provable independent associations between macro factors and stocks i.e. macro risk exposures for individual stocks and portfolios.

**2.2 The Qi MFERM Machine Learning Algorithm**

A standard OLS/GLS regression would lead to non-intuitive and spurious results that would arise when faced with a multi-collinearity and canonical collinearity that exists with macro factors. The Partial Least Squares Regression (PLSR) technique overcomes the multicollinearity problem that would arise in a standard linear regression analysis, where one attempts to regress security returns directly against many macro factors that have collinearity.

Qi employs a version of a mathematical technique called Partial Least Squares Regression analysis (PLSR) to accommodate the large number of macro factors that are potentially relevant in driving a given security, many of which may share a high degree of collinearity. Specifically, PLSR searches for a set of components (also called latent vectors) that performs a simultaneous decomposition of the response and predictor variables with the constraint that these components explain as much of the co-variance between them. We believe that this also leads to more intuitive results for the investor and risk practitioner given the algorithm emphasis on maintaining the predictor/response relationship even in high-dimensionality problems with multi-collinearity.

In addition to producing uncorrelated linear combinations of the original variables (*scores*, or latent variables), PLSR also provides a natural means of vastly compressing the data with little loss of information. **Figure 1** highlights the main difference between traditional PCA and PLSR. PLSR offers a significant improvement in explaining variation but also the directionality between the response and predictors resulting in a stable and more intuitive understanding of the factors.

In the standard approach, with many variables, the danger is always overfitting the model. Since PLSR uses only a subset of all the predictors for regression, it achieves dimensionality reduction by substantially lowering the effective number of parameters characterizing the underlying model. This concentration of most of the signal into a few principal components also referred to as latent vectors (LV1, LV2, ...) increases the signal-to-noise ratio in the fit and stabilizes the solution. As such Qi standardizes the usage to the first three latent vectors (LV1, LV2 & LV3) to maximize predictability and reduce overfitting.

In its standard form, the PLSR technique is widely used in the scientific community, most notably in chemometrics, bioinformatics, neuroscience, and anthropology. PLSR has already been employed widely in the finance industry to forecast market returns and solve other forecasting problems that have large numbers of predictor variables with collinearity.

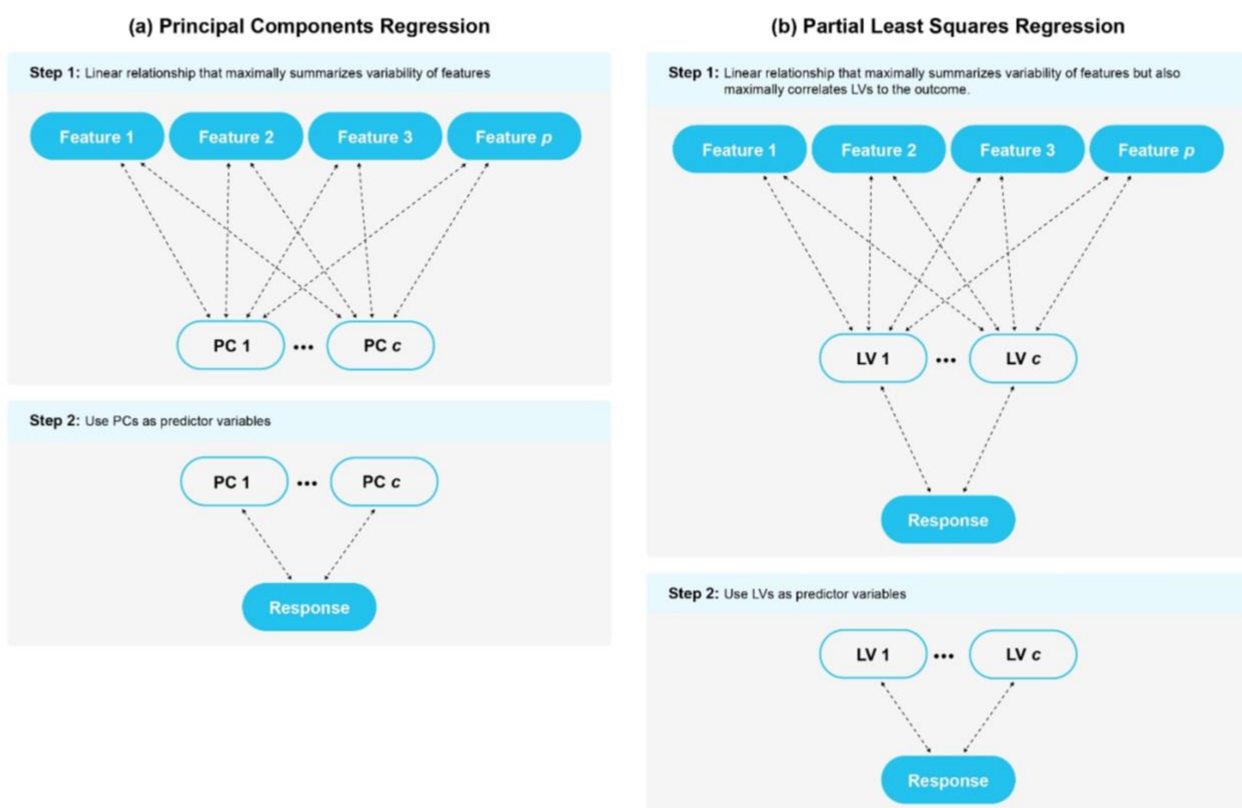


*FIG. 1: Graphical depiction of the difference between PLS and PCR methodologies*

## 2.3 The Qi MFERM Data Model

**a. Input Data Layer**

1. Convert all asset prices into a series of asset Returns.
2. Macro Factor (predictor) returns are adjusted to take into account their native units (i.e. price or spread based instruments as shown in the Appendix) to provide daily percentage changes and further standardized to have unit variance.
3. Factor Bucketing
    - Principal Component Analysis (PCA) is used to combine several descriptors underlying a factor and the first principal component (PC1) is taken as the new factor e.g. global Central Bank Expectations may be represented by the first principal component of a PCA that combines regional Bank Expectations within in a global model context. This method is only required when multiple descriptors exist for a factor.

**b. QI MFERM Machine Learning Layer (Partial Least Squares Regression)**

1. Calculate Latent Variable weights that maximizes covariance between predictors and response and normalize weight to unit length.
2. Each Latent Variable is a combination of the initial predictor variables.
3. Compute loadings which relate the initial predictor variables to the Latent Variable.
4. Deflate Predictor matrix to remove information in predictors that has been explained by current Latent Variable (LV)
5. Compute loadings for the response variable that captures the amount of variance explained by the current Latent Variable (LV).
6. Deflate the response variable to remove information already explained by current LV.
7. Repeat steps 1-6 for desired number of LVs.
8. Calculate Predictor Coefficients/Sensitivities **(**β**)** to directly relate the response variable to the predictors by combining the weights and loadings in steps 1-7.
9. Asset Returns may then be estimated using the equation below.

$$Ra = \alpha + \beta 1t * [LV1] + \beta 2t * [LV2] + \beta 3t * [LV3] + \varepsilon t$$

where

- Ra is Asset Return
- βn are the latent variable betas or exposures.

- Each latent variable is a linear combination of the original factors. Qi retains the information in the first 3 latent variables (LV1, LV2, LV3)

  Lookback Windows

  - Regression Window: 250 days (1 Year)
  - Standardizing Window: 250 days (1 Year)
  - Covariance Window: 125 days with exponential decay (6 months – 90d half-life)

**Refer to the Appendix for further details on the mathematical treatment of Qi PLSR.**

**c. QI MFERM Output Layer**

1. Factor Exposure Sensitivities for Estimation Universe
2. Factor Variance-Covariance Matrix

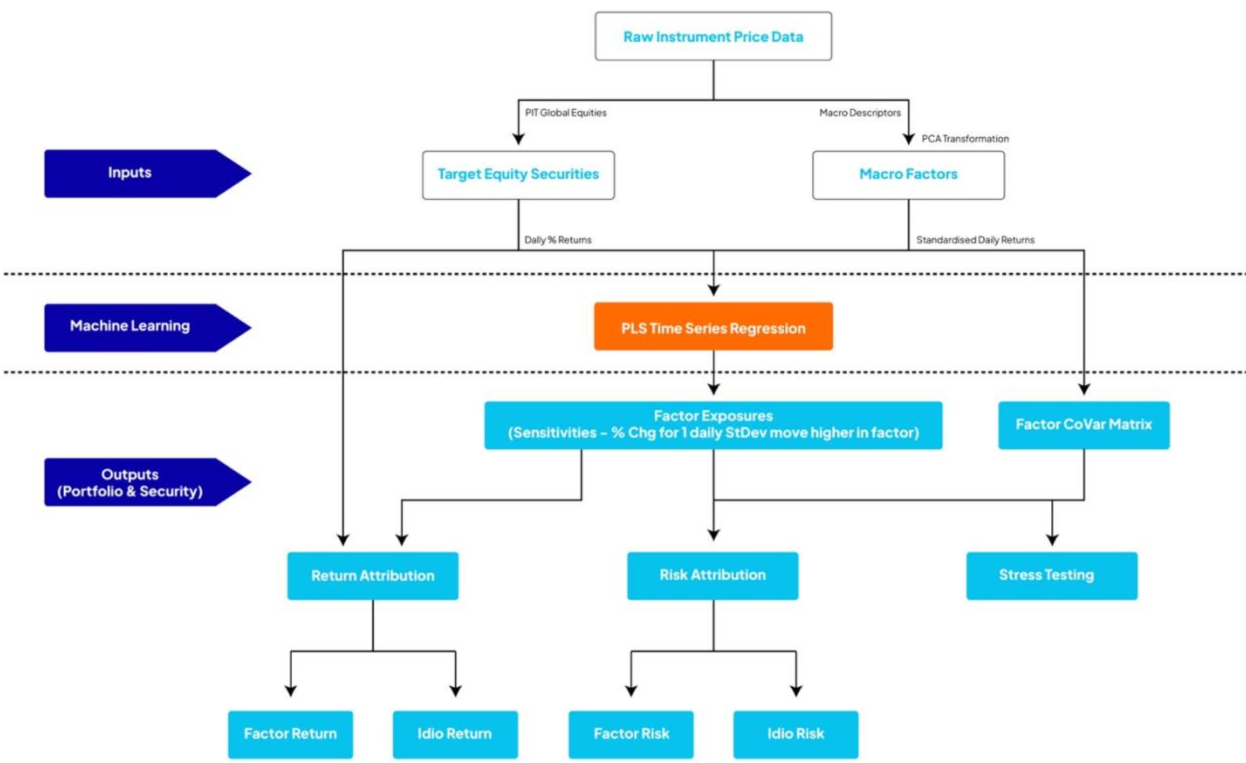



*FIG. 2: Data flow for model estimation*

## 2.4 Qi MFERM Risk Predictions and Return Attribution (Native Format)

Qi MFERM decomposes portfolio risk and return into two components: that which can be explained by our macro factor information set (including or excluding the market) and that which is due to the idiosyncratic nature of the securities in the portfolio. These are referred to as the factor and specific return, respectively.

As discussed above, the machine learning algorithm applied to the standardized daily returns of the macro factors and the asset yields the factor exposure sensitivities. Return attribution is a function of the factor exposures and daily macro factor returns. Risk attribution is a function of the factor exposures and the covariance matrix of the macro factors themselves. To estimate a portfolio's risk, we must consider not only the security or portfolio's exposures to the factors, but also each factor's risk and the covariance or interaction between factors.

Below, we highlight the key formulas applied to attribute portfolio risk and return.

**MFERM's risk and return attribution assumptions:**

- Risk metric is volatility: $\sigma$
- Stock risk is made of 2 *independent* components:
  - a *factor component*, $\sigma_f$, that is a function of the macro factors,
  - and a *specific component*, $\sigma_s$, particular to this stock.
- Factor return attribution at time "t" is the predicted stock / portfolio return (out-of-sample), using "t - 1" sensitivities (exposures), given we know the factor returns at "t"

Let us define $r_{T_{i_t}}$, as the total return of stock "i" at time "t". Let us further define a *linear* macro risk model with "k" factors, non-necessarily all independent (we dropped the time index to avoid cluttering the formulae),

$$r_{T_i} = X_i^t\, R_f + r_{S_i},$$

consisting of 2 independent components,

- Factor component: $$f_i = X_i^t\, R_f,$$

- Specific component: $$s_i = r_{S_i},$$

where we have grouped the sensitivities (exposures), $x_{j_i}$ of stock "i" to factor 1, 2, … k, into vector $X_i$, and the macro-factor returns into vector $R_f$,

("t" in the exponent means transpose and capital letters represent matrices).

Directly from our model construction we also define $a_{i_t}$,

$$a_{i_t} = X_{i_{t-1}}^t \, R_{f_t},$$

as the factor return attribution of stock "i" at time "t", or the stock movement at time "t" attributable to the factor returns also at time "t". However, we compute the factor return attribution using the sensitivities of the previous day ("t - 1"), making this estimate an out-of-sample (prediction) estimate.

Let us assume our macro risk model employs a model with "k" factors, non-necessarily all independent.

As result of the above assumptions, for an individual stock "i", total stock risk may be defined as,

$$\sigma_{t_i} = \sqrt{\sigma_{f_i}^2 + \sigma_{s_i}^2},$$

where the components were assumed independent.

We can write the *factor variance* of stock "i" in a very compact way using matrix algebra

$$\sigma_{f_i}^2 = X_i^t \, \Sigma_f \, X_i,$$

where,

$X_i$ groups the sensitivities (exposures), $x_{j_i}$ of stock "i" to factor 1, 2, … k, into a vector of exposures

$\Sigma_f$ is the factor co-variance matrix

For detailed calculations please refer to the Appendix: *Risk & Return Attribution Calculation Reference*

**2.5 Qi MFERM Cross-Sectional Model (Extension)**

Recognizing the need for cross-sectional analysis in the management of equity portfolio risks, Qi has extended the native model outputs to conform to a cross-sectional format that standardizes exposures across an estimation universe (refer to Section 4). This approach allows for risk estimation in a relative context i.e. relative to an estimation universe and easier integration and comparison with fundamental cross-sectional model infrastructure. The chart below shows the output layer for the cross-sectional extension.

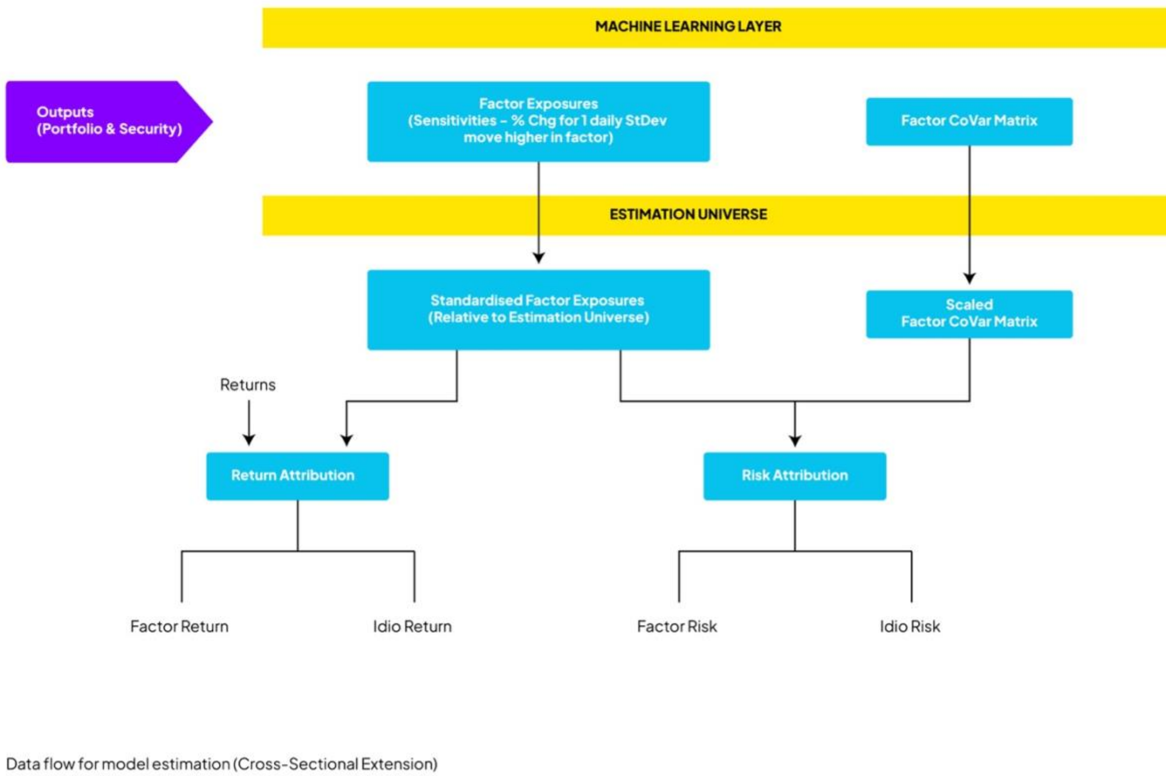



*FIG. 3: Data flow for model estimation (Cross-Sectional Extension)*

**Standardized Ranking System**

Qi calculates an equal-weighted cross-sectional mean and standard deviation across all assets in the respective estimation universe. Outliers are removed from the estimation universe, as explained below. Qi then uses a standardized ranking rather than traditional z-scoring and uses only the standard deviation to assess relative ranks across the universe. The standardized ranking process preserves the mean or average factor exposure of the estimation universe which is non-zero. Note that in typical cross-sectional models the mean exposure to a factor in the estimation universe is zero by virtue of its construction. In the Qi sensitivity-based process exposure sensitivities are calculated as part of a time-series regression and hence the universe mean sensitivity to a factor could be non-zero.

Ranked exposures for assets covered by the estimation universe are then provided as outputs of the cross-sectional variant. E.g. a rank of 2 to HY credit for a stock indicates that its sensitivity exposure to HY-credit is 2 times the cross-sectional standard deviation of the sensitivity of the estimation universe (which is non-zero).

**Scaled Cross-sectional Covariance Matrix**

To go along with the standardized ranked exposures in the cross-sectional variant of the Qi MFERM model, Qi provides a matrix that is scaled by the cross-sectional standard deviation of the estimation universe. This is simply a process of scaling the original native covariance matrix and there is no loss of information in this process.

We collect all sensitivity cross-sectional standard deviations into a vector

$$\mathrm{C}_s = \begin{bmatrix} \sigma_{C_1} \\ \sigma_{C_2} \\ \vdots \\ \sigma_{C_k} \end{bmatrix}$$

where $\sigma_{C_j}$ is the sensitivity cross-sectional standard deviation of factor "j". Next, we divide, elementwise, the matrix of sensitivities (exposures) by the vector $\mathrm{C_s}$,

$$X_c = X \oslash \mathrm{C_s},$$

where $X_C$ is the sensitivities standardized matrix. To keep units consistent across all entities, we also need to adjust the factors co-var matrix multiplying $\Sigma_f$, elementwise, by

$$\Sigma_{f\mathrm{c}} = \Sigma_f \odot [\mathrm{C_s}\, \mathrm{C_s^t}].$$

The factor returns vector also needs to be adjusted accordingly.

$$R_{f\mathrm{c}} = R_f \odot \mathrm{C}_s.$$

**2.6 Qi MFERM Risk Predictions and Return Attribution (Cross-Sectional)**

Given the new cross-sectional quantities, then the portfolio security "i" factor return attribution at time "t" reads

$$\mathrm{a}_{i_{c_t}} = X^t_{c_{i_{t-1}}} R_{f_{i_{c_t}}},$$

and total risk is still given by

$$\sigma_{Tc_i} = \sqrt{\sigma^2_{fc_i} + \sigma^2_{s_i}},$$

where

$$\sigma^2_{fc_i} = X_{c_i}\Sigma_{fc}\, X^t_{c_i}.$$

For detailed calculations please refer to the Appendix: *Risk & Return Attribution Calculation Reference*

**3. Stress Testing – Evaluate Impact of Macro Shocks**

Stress tests are designed to examine a variety of unlikely events that fall beyond the forecasting abilities of statistical models. The key aspect of any stress test is to select an appropriate scenario, yet this remains more of a judgment-driven exercise than a purely scientific one. Recognizing both the significance and complexity of scenario selection, we outline three approaches to streamline the process:

1. Historical scenarios
2. Uncorrelated user-defined scenarios
3. Correlated user-defined scenarios

**3.1 Historical scenarios**

A very common method for designing stress scenarios is to draw from historical events. For instance, we could examine the market and macroeconomic factor changes that occurred during the 2018 U.S.-China trade war and evaluate how they would influence our asset or portfolio today. Essentially, a historical stress test explores the question: how would my asset or portfolio respond if the U.S.-China trade war were to emerge again?

In 2018, President Donald Trump launched a trade war with China, imposing tariffs in response to perceived unfair trade practices. This led to heightened market volatility worldwide. Stock indices across Asia, Europe, and the U.S. experienced sharp declines following tariff announcements, driven by concerns over supply chain disruptions and a potential economic slowdown. Between October 3 and December 24, 2018, the S&P 500 (SPX) dropped by 20%.

During this period, macro factors had specific movements, which we can use to estimate the potential impact of a similar event, such as another trade war, on an asset or portfolio. In this analysis, we assume that factor shifts scale relative to their historical volatility rather than replicating absolute changes. To assess the impact on an asset, we use the following approach:

$$\text{Impact on asset} = \Sigma(\text{asset's exposure to factor x historical factor movement})$$

This methodology incorporates the actual factor movements observed between October 3, 2018, and December 24, 2018. The following example illustrates how the historical impact of the 2018 trade war would affect Tesla's (TSLA) current stock price.

Table A:

| | Vol-adjusted Factor Returns (2018-10-03 to 2018-12-24 in today's std) | TSLA Raw Exposures (2025-02-05 in % / std) | Shock * Exposures |
|---|---|---|---|
| **CB QT Expectations** | 8.0452 | 0.132123 | 1.06% |
| **CB Rate Expectations** | -16.9873 | 0.370068 | -6.29% |
| **Corporate Credit** | 25.6743 | -1.06544 | -27.35% |
| **DM FX** | 4.5274 | -0.0783183 | -0.35% |
| **Economic Growth** | -3.0611 | -0.131188 | 0.40% |
| **Energy** | -26.6703 | -0.145146 | 3.87% |
| **Forward Growth Expectations** | 7.7738 | -0.145044 | -1.13% |
| **Inflation** | -28.4806 | -0.624003 | 17.77% |
| **Metals** | -4.6679 | 0.140095 | -0.65% |
| **Real Rates** | -0.3935 | 0.0335415 | -0.01% |
| **Risk Aversion** | 11.9404 | -0.677825 | -8.09% |
| **10Y Yield** | -11.5103 | -0.0758936 | 0.87% |
| | | **Total Impact:** | **-19.90%** |

The combined impact of macro factors on TSLA's stock price would result in a -19.90% change. The most significant negative contribution comes from the Corporate Credit factor at -27.35%, partially offset by a positive 17.77% impact from the Inflation factor.

### 3.2 Uncorrelated user-defined scenarios

In the uncorrelated user-defined scenario, the user specifies a core factor value for one or more core factors, while all unspecified factors remain unchanged. The impact on the asset or portfolio is then evaluated based on these adjusted values. Below is an example illustrating the impact on Apple stock (AAPL) from a 50 bp widening of the Corporate Credit factor (represented by the US CDX HY descriptor). Since only the Corporate Credit factor is being adjusted, the corresponding change in the asset's value is calculated as follows:

Impact on AAPL = AAPL Exposure to Corporate Credit x Shock

- Model used: 'QI_US_MACRO_MT_1' Date: 2025-01-28
- AAPL Exposure to Corporate Credit: -0.2285% per 1 std dev
- Corporate Credit 1 std dev: 0.0577%
- 50 bp Shock expressed in Corporate Credit standardized factor returns (stds)

$$0.50 / 0.0577 = 8.6601$$

- Impact on AAPL: -0.2285 x 8.6601 = -1.98%

This quantifies how a shift in the Corporate Credit factor translates into a corresponding impact on AAPL.

Building on this single-factor analysis, this approach can be expanded to multiple core factors, with all unspecified factors remaining unchanged. The asset or portfolio is then evaluated based on these modified inputs. Below is an example demonstrating the impact on Apple stock (AAPL) from a 50 bp widening in the Corporate Credit factor, a 1% increase in the Inflation factor, and a 1% decline in the Economic Growth factor. The corresponding change in the asset's value is determined as follows:

Table B:

| | Shock Assumption (%) | 1 std dev (%) | Shock in std dev | AAPL Raw Exposures (% per std dev) | Impact on AAPL |
|---|---|---|---|---|---|
| **Corporate Credit** | 0.5 | 0.0577354 | 8.6602 | -0.228564 | -1.98% |
| **Economic Growth** | -1.0 | 0.0787489 | -12.6986 | -0.215034 | 2.73% |
| **Inflation** | 1.0 | 0.027211 | 36.7498 | -0.177654 | -6.53% |
| | | | | **TOTAL:** | **-5.78%** |

This calculation quantifies the combined effect on AAPL, resulting in a total impact of -5.78%.

**3.3 Correlated user-defined scenarios**

Since macro factors often move together, it is important to account for their correlations when designing realistic stress scenarios. For example, a widening in CDX High Yield credit spread (the Corporate Credit factor), signaling corporate stress, would naturally coincide with a rise in VIX (the Risk Aversion factor). To facilitate the creation of comprehensive user-defined scenarios, we have developed a framework that integrates these relationships. Users can specify an impact on a selected core factor, and our model can then estimate the expected shifts in other peripheral factors based on their historical correlations, leveraging our factor covariance matrix.

We assume that the returns of peripheral ($r_1$) and core ($r_2$) factors follow a joint normal distribution:

$$\begin{bmatrix} r_1 \\ r_2 \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}\right),$$

where:

$r_2$ represents the vector of core factor returns,

$r_1$ represents the vector of peripheral factor returns, and the covariance matrix has been partitioned, and

$\mu_1$ and $\mu_2$ represent the time-averaged returns of peripheral and core factors over a chosen look-back period (e.g., 125-days).

The covariance matrix is structured as follows:

- $\Sigma_{11}$: Variance-covariance matrix of peripheral factors
- $\Sigma_{22}$: Variance-covariance matrix of core factors
- $\Sigma_{12}$: Covariance between core and peripheral factors
- $\Sigma_{21}$: Transpose of $\Sigma_{12}$

The expected value of the peripheral factor returns given the core factor returns is:

$$E[r_1|r_2] = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(r_2 - \mu_2)$$

where:

$\Sigma_{22}^{-1}$ is the inverse variance matrix of the core factors and

$r_2$ is the shocks we apply to the core factors.

This equation predicts the movement of peripheral factors when the core factor experiences a user-defined change ($r_2$). The term $\Sigma_{12}\,\Sigma_{22}^{-1}$ acts as a regression beta, determining the sensitivity of peripheral factors to changes in core factors. This follows directly from the properties of the multivariate normal distribution, where conditional expectations are linear functions of the observed variables.

**Correlated scenario using a single factor: Widening of the Corporate Credit factor**

Let's revisit the first example from Section 3.2 and examine the impact of a 50 bp widening in the Corporate Credit factor on Apple (AAPL) stock. Table C below presents the covariance matrix of macro factors, and Table D provides AAPL's exposures to the macro factors.

Table C: Covariance matrix of macro factors (2025-01-28)

| | CB QT Expectations | CB Rate Expectations | Corporate Credit | DM FX | Economic Growth | Energy | Forward Growth Expectations | Inflation | Metals | Real Rates | Risk Aversion | 10Y Yield |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CB QT Expectations | 0.7234 | 0.2274 | 0.2968 | 0.0536 | 0.1792 | -0.1412 | -0.1872 | -0.0120 | -0.1635 | 0.0646 | 0.1289 | 0.1995 |
| CB Rate Expectations | 0.2274 | 1.0231 | 0.0117 | 0.0501 | -0.3202 | 0.2290 | -0.1901 | 0.2528 | -0.0383 | 0.0776 | -0.0817 | 0.6071 |
| Corporate Credit | 0.2968 | 0.0117 | 0.8510 | 0.3182 | 0.1078 | 0.0114 | -0.0534 | -0.0330 | -0.1603 | 0.1360 | 0.7661 | -0.0152 |
| DM FX | 0.0536 | 0.0501 | 0.3182 | 5.4515 | 0.0506 | -0.0697 | -0.2308 | 0.3025 | -0.3743 | 0.6630 | 0.5563 | -0.0293 |
| Economic Growth | 0.1792 | -0.3202 | 0.1078 | 0.0506 | 0.9841 | -0.0958 | 0.1114 | -0.1372 | 0.0313 | -0.0859 | 0.1022 | -0.2316 |
| Energy | -0.1412 | 0.2290 | 0.0114 | -0.0697 | -0.0958 | 1.1363 | 0.0516 | 0.0728 | 0.2893 | 0.1093 | -0.0166 | 0.1674 |
| Forward Growth Expectations | -0.1872 | -0.1901 | -0.0534 | -0.2308 | 0.1114 | 0.0516 | 1.1304 | -0.0191 | 0.1317 | -0.0622 | -0.1474 | -0.0806 |
| Inflation | -0.0120 | 0.2528 | -0.0330 | 0.3025 | -0.1372 | 0.0728 | -0.0191 | 1.1390 | 0.1638 | -0.1186 | -0.0573 | 0.3849 |
| Metals | -0.1635 | -0.0383 | -0.1603 | -0.3743 | 0.0313 | 0.2893 | 0.1317 | 0.1638 | 0.9118 | -0.1502 | -0.0707 | 0.0386 |
| Real Rates | 0.0646 | 0.0776 | 0.1360 | 0.6630 | -0.0859 | 0.1093 | -0.0622 | -0.1186 | -0.1502 | 0.8332 | 0.0644 | 0.0993 |
| Risk Aversion | 0.1289 | -0.0817 | 0.7661 | 0.5563 | 0.1022 | -0.0166 | -0.1474 | -0.0573 | -0.0707 | 0.0644 | 1.3042 | -0.1844 |
| 10Y Yield | 0.1995 | 0.6071 | -0.0152 | -0.0293 | -0.2316 | 0.1674 | -0.0806 | 0.3849 | 0.0386 | 0.0993 | -0.1844 | 0.7471 |

Table D: AAPL's exposures to macro factors

| | AAPL Raw Exposures (% per std dev) |
|---|---|
| CB QT Expectations | 0.016068 |
| CB Rate Expectations | 0.009249 |
| Corporate Credit | -0.228564 |
| DM FX | -0.011948 |
| Economic Growth | -0.215034 |
| Energy | -0.086132 |
| Forward Growth Expectations | 0.312278 |
| Inflation | -0.177654 |
| Metals | 0.059161 |
| Real Rates | -0.115005 |
| Risk Aversion | -0.325431 |
| 10Y Yield | 0.143877 |

Using the covariance matrix and AAPL's exposures to macro factors, we can calculate the total impact on AAPL stock price for a 50 bp widening of the Corporate Credit factor, which is -5.17%, as shown below.

Table E: Correlated scenario impact on AAPL

| | Impact on AAPL |
|---|---|
| CB QT Expectations | 0.048% |
| CB Rate Expectations | 0.003% |
| Corporate Credit | -1.979% |
| DM FX | -0.041% |
| Economic Growth | -0.250% |
| Energy | -0.011% |
| Forward Growth Expectations | -0.166% |
| Inflation | 0.044% |
| Metals | -0.096% |
| Real Rates | -0.164% |
| Risk Aversion | -2.547% |
| 10Y Yield | -0.008% |
| | **-5.17%** |

The first example for Uncorrelated Scenarios in Section 3.2 showed a -1.98% impact. In comparison, the Correlation Scenario results in a greater downside. This is primarily due to the correlation between the Corporate Credit factor and the Risk Aversion factor, which amplifies the negative effect.

Taking this a step further, the correlated stress test framework can be extended to analyze scenarios involving multiple core factors. Next, let's examine the impact on an asset price driven by multiple core factors.

**Example 3.5: Correlated stress using multiple factors: Widening of Corporate Credit factor and rise in Inflation factor**

Examining the impact of a 50 bp widening in the Corporate Credit factor alongside a 0.5% increase in the Inflation factor on Apple (AAPL) stock, we find that the combined impact is -6.82%, as shown in Table F below.

Table F: Impact on AAPL from a 50 bp Widening in Corporate Credit and a 0.5% Increase in Inflation factor

| | Impact on AAPL |
|---|---|
| CB QT Expectations | 0.048% |
| CB Rate Expectations | 0.041% |
| Corporate Credit | -1.979% |
| DM FX | -0.102% |
| Economic Growth | 0.218% |
| Energy | -0.115% |
| Forward Growth Expectations | -0.275% |
| Inflation | -3.264% |
| Metals | 0.057% |
| Real Rates | 0.050% |
| Risk Aversion | -2.400% |
| 10Y Yield | 0.897% |
| | **-6.82%** |

The breakdown reveals that the downward pressure on AAPL is primarily driven by Inflation, Corporate Credit, and Risk Aversion factors.

## 4. Data Quality and Outlier Corrections

Qi sources daily price data from a variety of third-party data vendors including Morningstar, IHS Markit, Macrobond, and Now-casting. Each day, we perform a "*raw data cleaning/verification*" procedure which includes:

- Identification and correction of outliers, including removal if required
- Creation of "*adjusted*" time series by applying corporate actions adjustment coefficients (equities only).

We also take measures to prevent sensitivity (exposure) outliers leaking in the cross-sectional estimation process.

We set off by removing obvious outliers like NaNs or values whose absolute value is very large. This defines our base set of estimates. We then continue:

1- We compute the mean and standard deviation of the estimation set.
2- We z-score the values.
3- We check the z-scores for any values outside of the acceptable sigma range [-4, +4].
4- If we find values outside the acceptable range, these are trimmed, and we re-start at step 1, unless the percentage of sensitivities rejected is larger than 12% of the entire set. In this case we mark the full set as "*bad*" and reject it.
   If all z-scores are inside the "*good*" range [-4, +4], then we divide all values in the base set of estimates by the standard deviation and terminate. The mean value is returned but cross-sectional sensitivities are not de-meaned.

**5. Model Coverage and Access**

Model coverage is available since 2009. Total coverage shown in the table below refers to the total point-in-time coverage count of unique instruments for each MFERM model (US, Europe, Asia-Pacific, and Global models).

**Model Coverage (Equities)**

| **MFERM Model** | **Total Instruments Available** |
|---|---|
| US (with and without Market) | 13,086 |
| Europe (with and without Market) | 2,584 |
| APAC (with and without Market) | 3,621 |
| Global (with and without Market) | 13,204 |

Qi's choice of estimation universe for the cross-sectional variants is designed to offer representative coverage in the four regional models that are offered (US, Europe, Asia-Pacific, and Global). For each of these regions, model coverage is Russell 3000, STOXX Europe 600, MSCI Asia Pacific, and MSCI ACWI.

**Cross-Sectional Estimation Universe**

| **Index** |
|---|

| |
|---|
| Russell 3000 |
| STOXX Europe 600 |
| MSCI Asia Pacific |
| MSCI ACWI |

**Access Files**

The Qi infrastructure has made the entire analytical data set available to clients through API and SFTP, for all regional models:

1. Factor Covariance Matrix (native & cross-sectional adjusted)
2. Descriptor & Factor Standard Deviation
3. Factor Exposures (native & cross-sectional adjusted)
4. Exposure Errors (native & cross-sectional adjusted)
5. Standardized Factor Returns
6. Factor/Specific/Total Return & Risk attribution

**6. Factor and Descriptor Definitions**

Factors can contain several individual descriptors that best represent the macro scenario being captured. Where there are multiple descriptors for a factor, Qi calculates the first Principal Component from the descriptor timeseries and uses this as the factor timeseries. For the US Risk Model, every factor has one descriptor. For the US model, this 12-large macro factor information set is described below. These factors have been selected on the hypothesis that stock price variance can be well explained by the interplay of 3 broad influences – growth expectations, financial conditions and risk appetite.

Please be sure to refer to the appendix for a detailed definition of the underlying macro factors, definitions, and their interpretations. Qi models are available across all geographic and economic regions and employ all or relevant subsets of the factors and descriptors described below and in the appendix. All regional models also allow for the addition of the market as an additional factor to isolate active macro factor exposures.

**Growth Expectations**

a. **Economic Growth:** Daily updated real GDP growth as measured by Now-Casting for the G3 – US, China & Eurozone.

b. **Metals:** Higher copper as a proxy for global economic activity. Metals prices are typically positively associated with risky assets and bond yields as they speak to the idea that the global economy is growing.
c. **Energy:** Energy price shifts have an impact on the economy and more directly on certain sectors. WTI Crude Oil prices are used to measure energy prices.
d. **Local Forward Growth Expectations**: This is measured by the shape of the relevant country's yield curve. For DM markets typically the shape of the yield curve between 5yrs & 30yrs. In some EM markets where liquidity diminishes for longer maturities, it may be the 2s10s yield curve that is captured. QE has distorted the classic interpretation, but the rule-of-thumb still stands: the curve flattens in a recessionary environment, steepens during periods of reflation.
e. **Local Inflation**: The inflation swap market for the relevant country. Higher inflation expectations are typically positive for risky assets & negative for Fixed Income instruments.

**Financial Conditions**

f. **Corporate Credit**: US, European & Japanese corporate credit spreads as measured by Credit Default Swaps. Both investment grade & High Yield credit are captured (depending on the country). Wider spreads (in basis points) indicate stress in credit markets. A positive relationship implies your asset benefits from increased credit stress.
g. **Nominal yields on 10-year government bonds:** Higher nominal yields are often a negative driver of risky assets.
h. **Real yields on 10-year government bonds**: Real yields in USD, EUR & JPY. Measured by nominal yield less inflation expectations at the 10y maturity in each currency.
i. **Central Bank Rate Expectations**: Slope of the relevant money market strip as measured by the spread between 1y1y forward yield & spot 1y yields. This effectively captures what money markets are discounting in terms of policy rates in the next 12-24 months, i.e. whether the Fed/ECB/BoE/BoJ are hiking or cutting rates & at what speed
j. **Local FX:** Captures the relevant DM currency for that model & its geography. A stronger currency on a trade weighted basis represents a tightening of financial conditions.
k. **Global CB QT Expectations:** Implied rate vol is used as a proxy for Central Bank (Fed/BoJ/ECB/BoE) Quantitative Tightening expectations. Higher rate vol speaks to increased QT expectations (like the 2013 Taper Tantrum for example). A positive relationship implies your asset benefits from a tighter monetary policy stance, presumably as it reflects a self-sustaining upswing in the economic cycle.

**Risk Appetite**

a. **Risk Aversion:** VIX & other "fear gauges" across DM & EM equity markets

## 7. Model Validation & Performance Statistics

**Estimation stability and quality of the predictive estimators (in-sample vs out-of-sample)**

To provide a measure of how well the observed outcomes are recovered by the model, Qi calculates the R-Squared (RSq), which is based on the proportion of the total variation of outcomes explained by the model. The value of RSq provides a measure of the global fit of the model. Specifically, RSq lies in the range [0; 1] and represents the proportion of variability in the outcome that may be attributed to some linear combination of the explanatory variables.

In such models, RSq is often interpreted as the proportion of response variation "explained" by the regressors in the model. Thus, RSq = 1 indicates that the fitted model explains all variability in the outcome, while RSq = 0 indicates no “linear” relationship between the response variable and regressors. Thus, an interior value such as RSq = 0.7 may be interpreted as follows: seventy percent of the variance in the response variable can be explained by the explanatory variables; the remaining thirty percent can be attributed to unknown, lurking variables or inherent variability.

**Qi Model Stats (SPX 500 – US Models)**

| | |
|---|---|
| Average RSq (monthly) | 34.6% |
| Bias Statistic (daily) | 0.94 |
| Bias Statistic (monthly) | 0.90 |

A key metric of the effectiveness and usefulness of a model is its predictive power, usually known as out-of-sample performance. Estimation stability is a key aspect of the model’s predictive power.

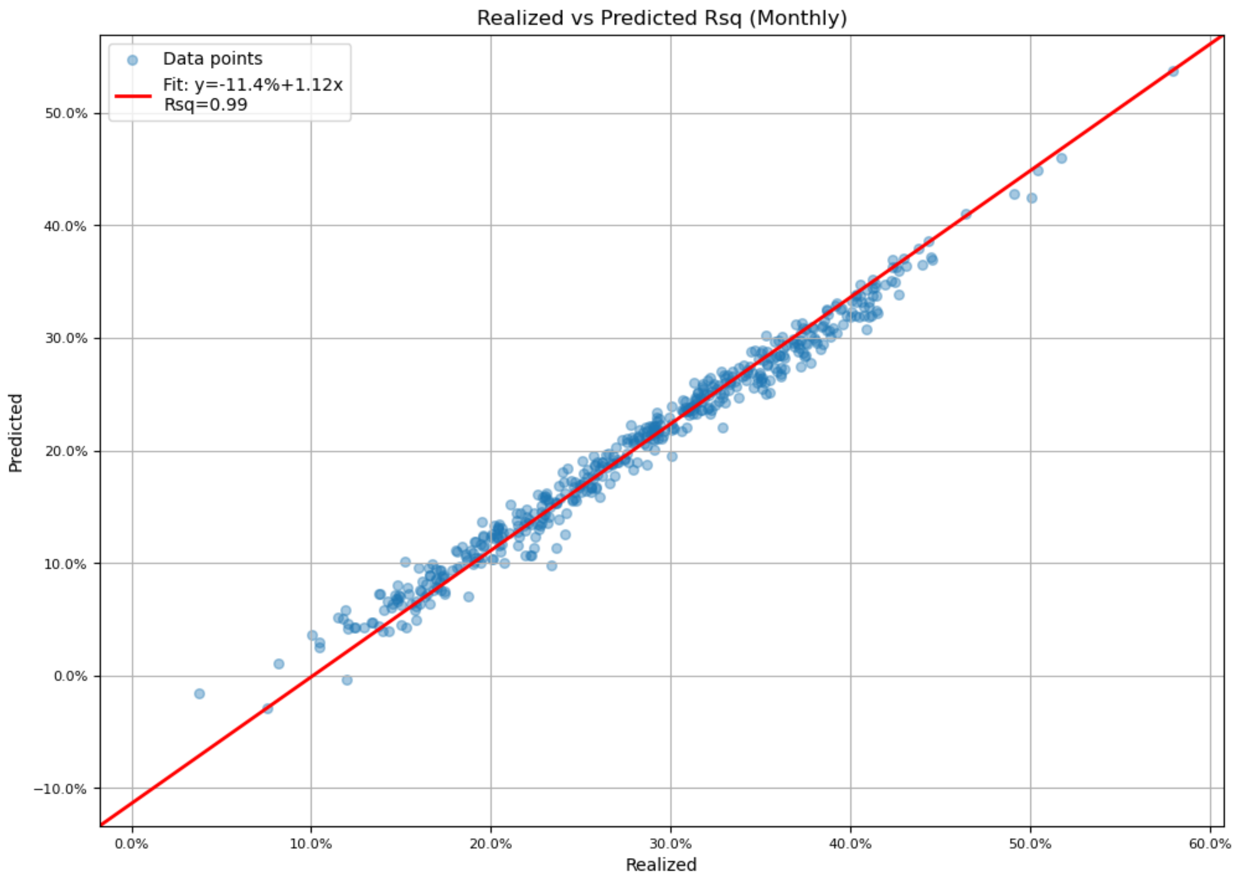



*FIG. 3*

The scatter plot above (Figure 3) compares the in-sample vs the out-of-sample R-squared. The in-sample R-squared is defined as the explanatory power of macro as a proportion of daily stocks returns using a 30d lookback inside the training period. As shown in the table above the average Rsq across the SPX 500 is about 35%. Simultaneously, we repeat the same Rsq calculation, but now using the factor exposures computed 1 month ago, when we didn't have access to current data (a forward prediction), keeping those exposures constant across the entire month. The R-squared of in-sample vs. out-of-sample is 99% which highlights the robustness / stability of the model generated exposures. In summary: using 1mth old factor exposures we can still be confident about the prediction capacity of macro explanatory power even if there is, as expected, some very mild and uniform degradation.

**Bias stats (single window)**

Another widely used method to validate the stability, and the accuracy, of the risk forecast is the "*bias statistic (single window)*" (please check appendix (*v*) for the mathematical details). The bias statistic can be read as the ratio of realized risk over the predicted one.

In our validation tests we have used a window of 1-month (only trading days) for calculating MFERM's *Bias Statistic (single window)* average across the universe of all stocks. The daily bias statistic is 94% of the time below its upper limit, meaning actual (realized) risk is 94% the time equal or less that our estimate.

## 8. Examples and Use Cases

The stated objective of Qi MFERM is to decompose an asset or portfolio's return and risk into explainable components to consider 3 core questions: Does macro matter? If macro matters where and which factors matter most? The follow on to which is, am I being compensated for taking that macro risk exposure? The schematic below highlights key applications.

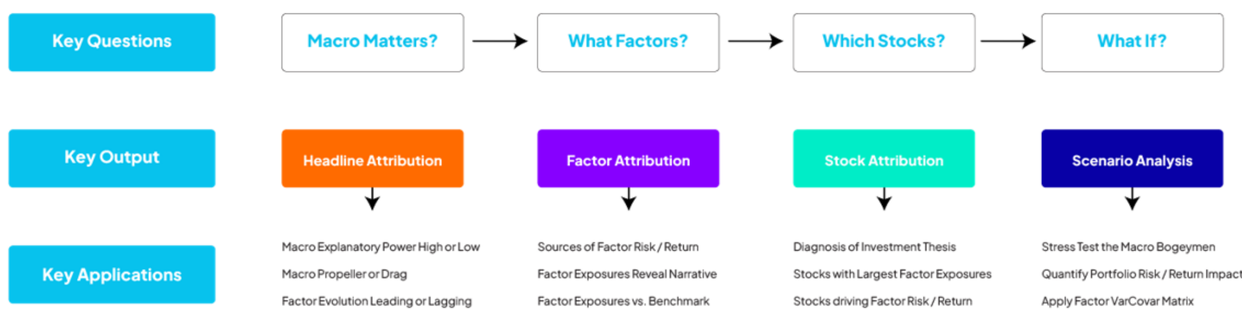



*FIG. 4: Reveal the Macro Anatomy*

Below, we provide 3 examples / use cases:

i. Return Attribution – Macro or idio? Which factors are tailwinds vs. headwinds?
ii. Risk Attribution - Macro or idio? Which factors drive volatility higher vs. lower?
iii. Portfolio Attribution – Dissect and diagnose unintended macro bets in a portfolio context

### 8.1 Return Attribution – Macro or idio? Which factors are tailwinds vs. headwinds?

**XLF Financial Sector ETF 26% Correction (12-Jan-22 to 12-Oct-22)**

The chart below shows the XLF Financials Sector ETF cumulative return from 12-Jan-22 to 12-Oct-22 – a period where the ETF saw a 26% correction. The Factor return accounted for -15.7% vs. a Specific return of -10.1%. In this case, Qi's factor information set comprises of the 12 macro descriptors. Users can choose to apply Qi's model including or excluding the market.

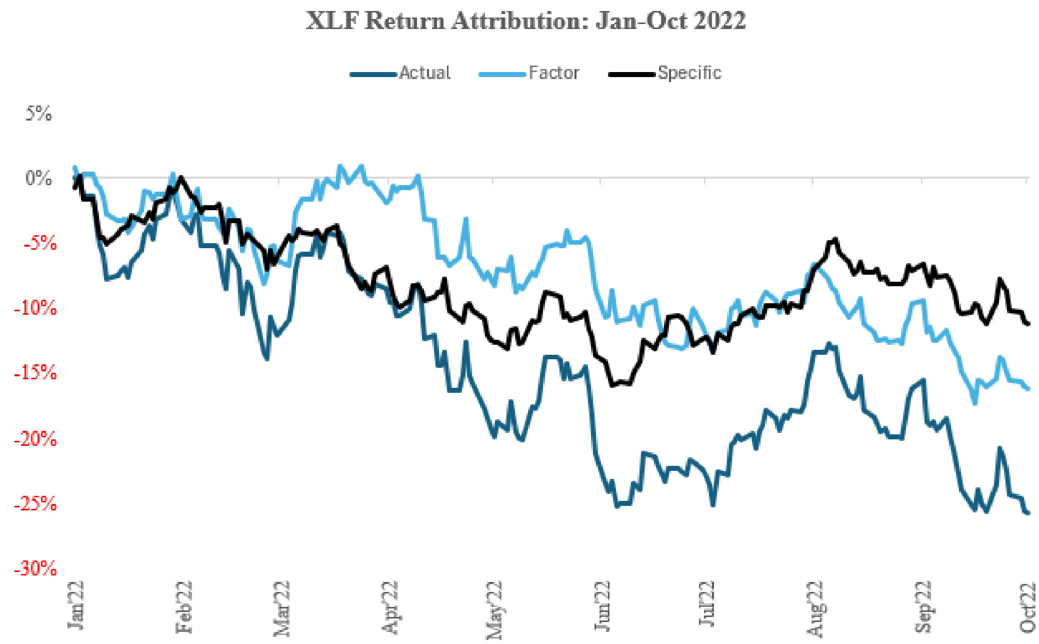



*FIG. 5*

The table below shows the anatomy of the Factor & Specific returns over this period. While the rise in US rates provided positive Factor returns over this period, this was overwhelmed by the drags from wider US HY corporate credit spreads, dollar strength, lower growth expectations and higher risk aversion.

**Factor Return Attribution: 12-Jan-22 to 12-Oct-22**

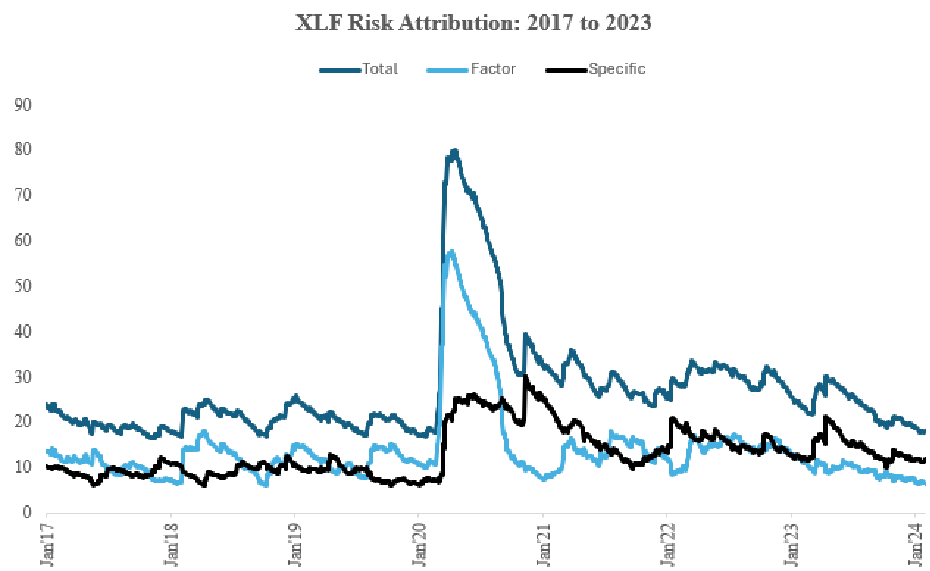
| **Attribution** | **% Return** |
|---|---|
| CB QT Exp | 1.9% |
| CB Rate Exp | -1.4% |
| Corporate Credit | -12.1% |
| DM FX | -8.5% |
| Real Rates | 6.0% |
| 10Y Yield | 2.6% |
| **Financial Conditions** | **-12.11%** |
| Economic Growth | 0.13% |
| Energy | 2.11% |
| Forward Growth Exp | -1.66% |
| Inflation | -0.28% |
| Metals | -1.02% |
| **Growth Expectations** | **-0.75%** |
| **Risk Aversion** | **-3.31%** |
| **FACTOR Return** | **-15.66%** |
| **SPECIFIC Return** | **-10.10%** |
| **SPOT Return** | **-25.75%** |

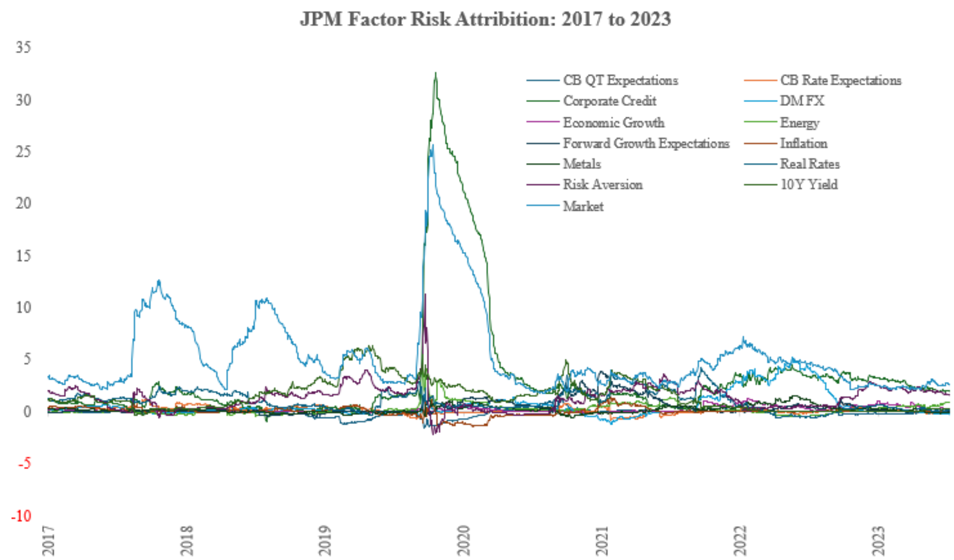
## 8.2 Risk Attribution - Macro or idio? Which factors drive volatility higher vs. lower?

**JPM (2016-2023)**

Risk attribution provides the user with the additional insight of which factors are most important to explain an asset's predicted volatility. Annualised volatility can also be split into 'Factor' i.e. explainable by macro factors and market, and 'Specific' i.e. idiosyncratic. In the case of JPM, note in the first chart below that Factors have a large bearing on JPM's overall volatility i.e. the gyration in overall vol mirrors Factor-driven vol. Specific vol, in contrast, is more stable.

The second chart shows the individual factors behind Factor risk. Factor risk jumped sharply during Covid (largely attributable to the jump in credit spreads), again during 2022 (higher credit spreads, stronger dollar), before dissipating through 2023 (easing in financial conditions). The third table provides a snapshot risk attribution as at 12-Mar-20.






**JPM Predicted Annualised Risk Attribution as at 12-Mar-20**

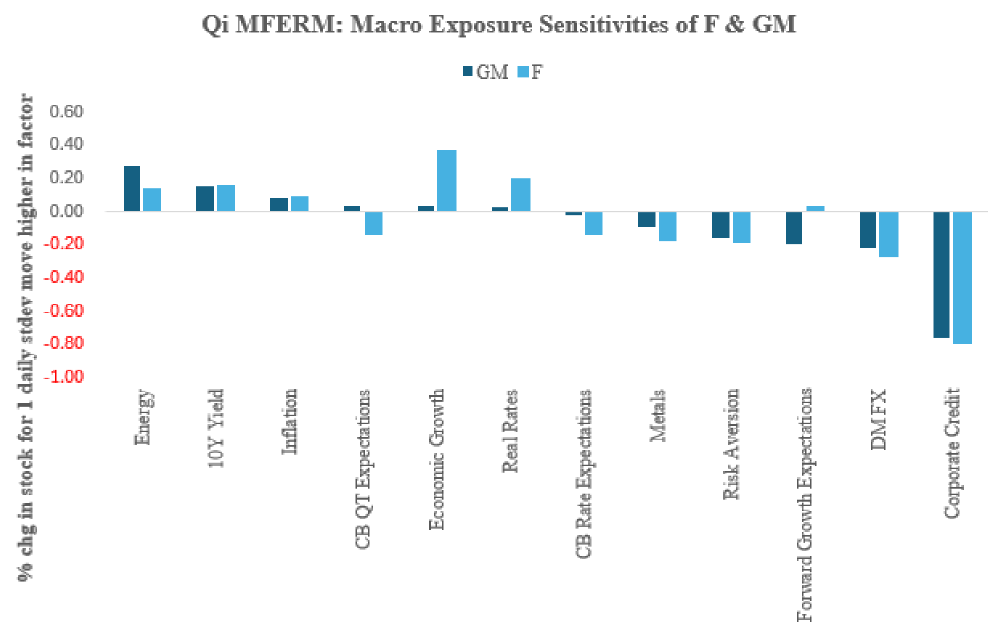
| **Attribution** | **%** |
|---|---|
| CB QT Exp | -0.7 |
| CB Rate Exp | 0.1 |
| Corporate Credit | 8.9 |
| DM FX | 0.9 |
| Real Rates | 0.4 |
| 10Y Yield | 4.1 |
| **Financial Conditions** | **13.7** |
| Economic Growth | 0.2 |
| Energy | 4.4 |
| Forward Growth Exp | 1.4 |
| Inflation | -0.8 |
| Metals | 0.2 |
| **Growth Expectations** | **5.3** |
| **Risk Aversion** | **7.0** |
| **Market** | **13.9** |
| **FACTOR Vol** | **40.0** |
| **SPECIFIC Vol** | **8.5** |
| **TOTAL Vol** | **48.4** |

### 8.3 Portfolio Attribution – Dissect and diagnose unintended macro bets in a portfolio context

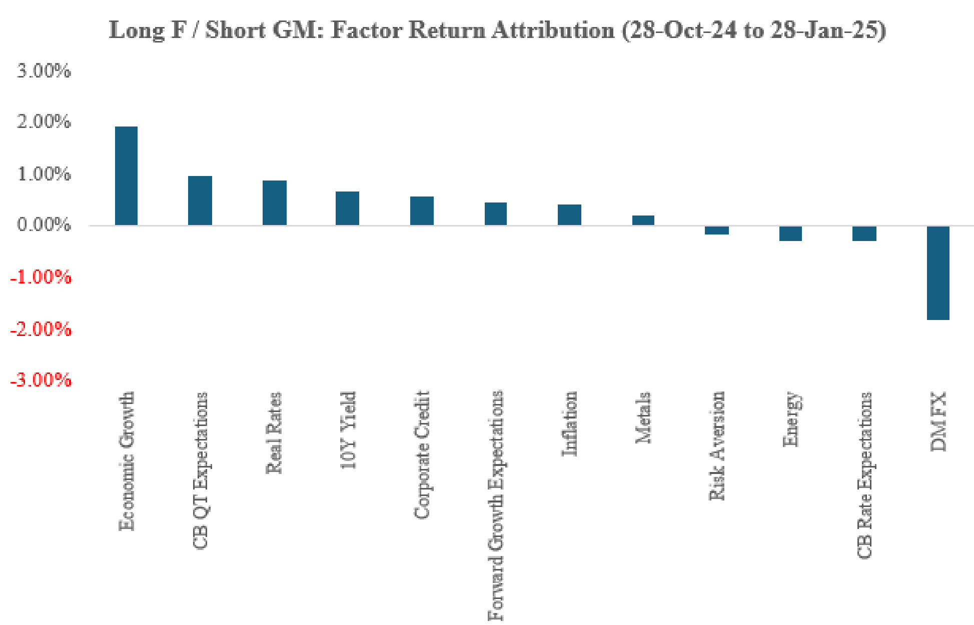
#### Unintended exposure in fundamental equity long / short pair trading – Ford vs. GM

The presumption is that the long / short pair Ford vs. GM has isolated alpha by removed other factor bets such as market direction, region, industry and style. Therefore, this pair trading approach should isolate your idiosyncratic view on the stock.

However, we show below that each have different exposures to the overall macroeconomic environment e.g. Ford is more geared to the economic cycle and is more export oriented than GM. F has notably higher exposure than GM to economic growth and real rates. Exposure shown below are as at 17-Jan-25.




If we consider the attributable factor return over the 3 month period Oct-24 to Jan-25, we see that stronger economic growth & higher real rates have been tailwinds for Ford relative performance but dollar strength a headwind.

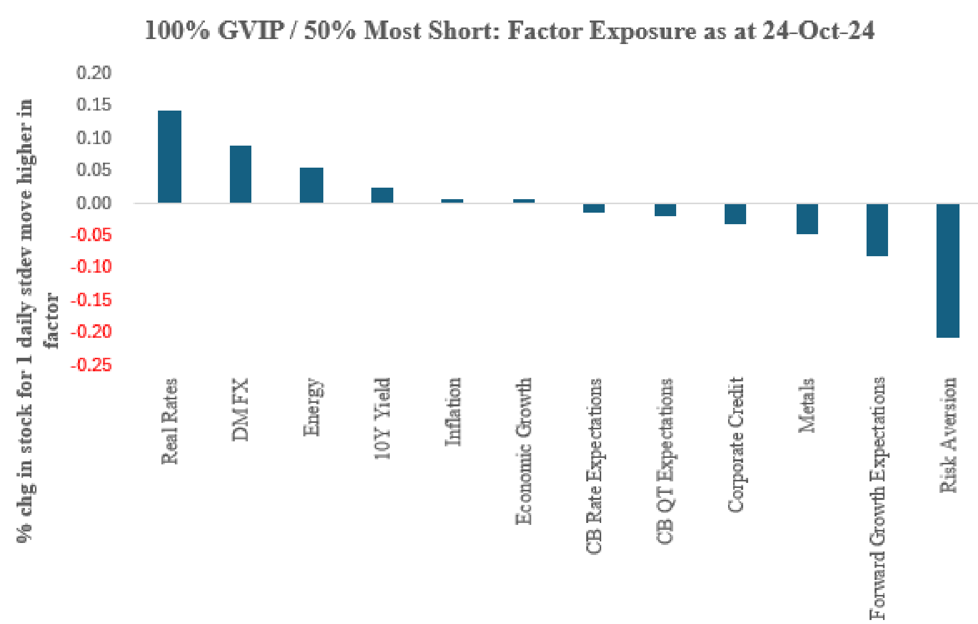


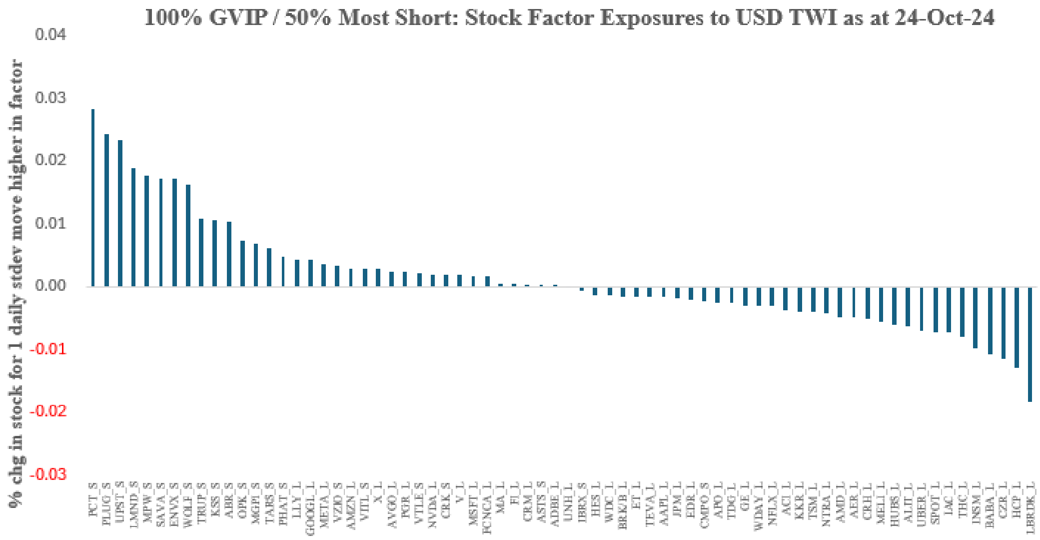
Unintended exposure in fundamental equity long / short portfolio – 100% long GS HF VIP stocks / 50% short highest short interest stocks

As of October 2024, this specific portfolio was net long Technology, Financials, Consumer Discretionary and Industrials; and net short Consumer Staples, Real Estate and Energy.

Over the period July to October 2024, positive idiosyncratic returns had been more than offset by macro factor headwinds keeping spot returns range-bound. The portfolio wanted higher real rates, a stronger dollar, lower risk aversion and a flatter 5s30s curve i.e. it can withstand tightening in financial conditions as long as supported by reflation. From July to October 2024, factor vol had jumped from 20% of total portfolio vol to almost 40% i.e. macro influence was rising.

For a portfolio, Qi MFERM will identify return / risk attribution and factor exposures to the single stock level. From this data a mosaic of charts can be produced. Two example snapshots are shown below. This portfolio's factor exposures as at 24-Oct-24 and USD TWI exposures attributed to the single stock level.






## 9. Appendix

*(i) PLSR methodology – technical details*

Partial Least Squares Regression (PLSR) is a statistical method used for modelling relations between sets of observed variables by means of latent variables. When you're dealing with one target variable, the method is often referred to as PLS1. Here's a step-by-step breakdown of how PLS regression is implemented in Qi's Macro Risk Model:

Let **X** denote the n x p matrix of p predictor variables across n observations, and **y** denote the vector of the response variable (n x 1). Qi's standard risk model uses p=13 factors over a lookback window of n=250 days.

**Standardizing**: Before matrix **X** is formed, we standardize the predictor timeseries by their 250-day rolling standard deviations. This ensures that all variables contribute equally to the analysis.

Begin iterative process:

1. Calculate the weights **w** for the latent variable (principal component) that maximizes the covariance between the predictors **X** and the response **y.**

$w = X^T y / (y^T y)$

$\mathbf{X^T y}$ computes the covariance between the predictors in **X** and the response **y**. This covariance matrix is then scaled by the inverse of the variance of **y**, adjusting the scale of the covariance matrix to the scale of the variance of **y**.

The weights are then normalized to ensure **w** has unit length, $\mathbf{w} = \mathbf{w} / \hat{\mathbf{w}}$ **.**

2. Compute the scores **t**, which are the projections of **X** along **w**. This is the time series for the latent variable (component). Each latent variable is a linear combination of the initial predictor variables.

$t = Xw$

3. Compute the loadings **p**, which relates the original predictor variables to the scores. These tell us how much each predictor variable contributes to the variance in the scores **t**.

$p = X^T t / (t^T t)$

4. Deflate the predictor matrix **X**. This step removes the information in **X** that has been explained by the current component.

$X = X – tp^T$

5. Compute loading c for the response variable. This is the amount of variance in **y** that has been explained by the current component.

$c = y^T t / (t^T t)$

6. Deflate **y** based on this loading. This removes the information in **y** that has been explained by the current component.

$\mathbf{y} = \mathbf{y} – \mathbf{t}c$

Repeat steps 1 – 6 for desired number of components. In Qi's Risk Model 3 components are retained.

**Calculate predictor coefficients:** The regression coefficients **β** for the predictors in **X** can be calculated by combining the weights and loadings across all extracted components.

$$\beta = W(P^T W)^{-1} c$$

Where **W** is the matrix of predictor weights in each component, **P** is the matrix of loadings and **c** is the vector of response loadings. This makes the component betas $\boldsymbol{\beta}\_\mathbf{c} = (\mathbf{P}^T\mathbf{W})^{-1}\mathbf{c}$.

*(ii) Factor Buckets and Factors Glossary*

| Qi US Macro Factor Equity Risk Model | |
|---|---|
| US Asset Coverage | Major US Indices<br><br>ETFs: Index, Sector, Thematic<br><br>Single stocks: Russell 3000 point in time since 2009 |
| Macro Factors | 13 including Market Factor, 12 for No-Market |
| Regression Window | 250-days (1 Year) |
| Standardizing Window | 250-days (1 Year) |
| Historical Data Start Date | Jan 2009 |
| Methodology | Partial Least Squares Regression with first 3 Latent Variables |
| Descriptor Combination Scheme | First Principal Component where multiple Descriptors used within a single Factor |

**Note: Qi US Macro Factor Equity Risk Model with No Market is also available for investors wanting to exclude the broad equity market and focus on pure macro factor analysis. Further, Models are also available for Global, European and Asia Pacific. Please ask us for more details.**

*(iii) Risk & Return Attribution Calculation Reference*

MFERM's risk and return attribution assumptions:

- Risk metric is volatility: $\sigma$
- Stock risk is made of 2 *independent* components:
  - a *factor component*, $\sigma_f$, that is a function of the macro factors,
  - and a *specific component*, $\sigma_s$, particular to this stock.

Factor return attribution at time "t" is the predicted stock / portfolio return (out-of-sample), using "t - 1" sensitivities (exposures), given we know the factor returns at "t"

Let us define $\mathrm{r}_{T_{i_t}}$, as the total return of stock "i" at time "t". Let us further define a linear macro risk model with "k" factors, non-necessarily all independent (we dropped the time index to avoid cluttering the formulae),

$$\mathrm{r}_{T_i} = X_i^t\, R_f + r_{S_i},$$

consisting of 2 independent components,

- Factor component: $f_i = X_i^t\, R_f,$

- Specific component: $s_i = r_{S_i},$

where we have grouped the sensitivities (exposures), $x_{j_i}$ of stock "i" to factor 1, 2, … k, into vector $X_i$, and the macro-factor returns into vector $R_f$,

$$X_i = \begin{bmatrix} x_{1_i} \\ x_{2_i} \\ \vdots \\ x_{k_i} \end{bmatrix}; \quad R_f = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_k \end{bmatrix}$$

("t" in the exponent means transpose and capital letters represent matrices).

Directly from our model construction we also define $\mathrm{a}_{i_t}$,

$$\mathrm{a}_{i_t} = X_{i_{t-1}}^t\, R_{f_t},$$

as the factor return attribution of stock "i" at time "t", or the stock movement at time "t" attributable to the factor returns also at time "t". However, we compute the factor return attribution using the sensitivities of the previous day ("t - 1"), making this estimate an out-of-sample (prediction) estimate.

For an individual stock "i", total risk may be defined as,

$$\sigma_{\mathrm{T_i}} = \sqrt{\sigma_{\mathrm{f_i}}^2 + \sigma_{\mathrm{s_i}}^2},$$

where the components are assumed independent.

The factor variance of stock “i” may be written in a very compact way using matrix algebra

$$\sigma_{f_i}^2 = X_i^t \, \Sigma_f \, X_i,$$

where “t” means transpose.

Matrix

$$\Sigma_f = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1k}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2k}^2 \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{k1}^2 & \sigma_{k2}^2 & \cdots & \sigma_{kk}^2 \end{bmatrix},$$

is the factor returns co-variance matrix defined by the factor’s co-variance operator:

$$\sigma_{ij}^2 = E[(f_i - E[f_i])(f_j - E[f_j])],$$

where E[] is the expected value operator (and not a matrix). This is a symmetrical positive definite square matrix with k (k is the number of factors in our model) rows and k columns, where $\sigma_{11}^2$ is the variance of the first factor, $\sigma_{kk}^2$ is the variance of the k factor, etc.

This framework can be easily extended to the risk analysis of portfolios. Imagine we have a portfolio made of “n” constituents with weights:

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix},$$

and sensitivities:

$$X_p = \begin{bmatrix} x_{1_1} & x_{1_2} & \cdots & x_{1_k} \\ x_{2_1} & x_{2_2} & \cdots & x_{2_k} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n_1} & x_{n_2} & \cdots & x_{n_k} \end{bmatrix},$$

where each row “i” contains the “k” sensitivities of stock “i”. The portfolio factor return attribution at time “t”, now reads,

$$a_{p_t} = W^{t} X_{t-1}^{t} R_{f_t}.$$

For the portfolio risk analysis, we also split *total risk,* $\sigma_{t_p}$, into the same components as the for the individual stock, namely: *factor* $\sigma_{f_p}$ and *specific* $\sigma_{s_p}$,

$$\sigma_{T_p} = \sqrt{\sigma_{f_p}^2 + \sigma_{s_p}^2}.$$

The portfolio factor variance can be written using the exact same expression as for the single stock just replacing the individual sensitivities matrix, $X_i$ by a new one, $X_w$, defined as follows,

$$X_w = X_p^t W,$$

The new expression for the portfolio factor variance reads,

$$\sigma_{f_p}^2 = X_w^t \Sigma_f X_w.$$

Replacing $X_w$ definition into the above expression, we get,

$$\sigma_{f_p}^2 = W^t X_p \Sigma_f X_p^t W.$$

Defining a new matrix,

$$C_f = X_p \Sigma_f X_p^t,$$

We recover a familiar form for risk,

$$\sigma_{f_p}^2 = W^t C_f W.$$

The portfolio specific risk component can also be expressed in the language of matrix algebra. Defining $\Sigma_s$ as a n x n diagonal matrix where each diagonal element is the respective portfolio constituent specific variance $\sigma_{s_i}^2$,

$$\Sigma_s = \begin{bmatrix} \sigma_{s_1}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{s_2}^2 & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{s_n}^2 \end{bmatrix},$$

then the portfolio specific risk component reads,

$$\sigma_{s_p}^2 = W^t \, \Sigma_s \, W.$$

This expression for the portfolio specific risk is applicable only if we assume that the *individual specific risk of each portfolio constituent is independent of all others*.

Bringing both components together, the portfolio total variance reads,

$$\sigma_{\mathrm{T_p}}^2 = \sigma_{f_p}^2 + \sigma_{s_p}^2 = W^t \left[ X_p \Sigma_{\mathrm{f}} X_p^t + \Sigma_{\mathrm{s}} \right] W.$$

Defining a new matrix $\mathrm{C_T}$ as,

$$\mathrm{C_T} = \left[ X_p \Sigma_{\mathrm{f}} X_p^t + \Sigma_{\mathrm{s}} \right] = \mathrm{C_f} + \Sigma_{\mathrm{s}},$$

it is also possible to reduce the portfolio total variance to a well know formula ideal for constructing a portfolio optimization algorithm,

$$\sigma_{\mathrm{T_p}}^2 = W^t \, \mathrm{C_T} \, W.$$

**Cross-sectional Extension**

To go along with the standardized ranked exposures in the cross-sectional variant of the Qi MFERM model, Qi provides a co-var matrix that is scaled by the cross-sectional standard deviation of the estimation universe. This is simply a process of scaling the original native covariance matrix and there is no loss of information in this process. We collect all sensitivity cross-sectional standard deviations into a vector

$$\mathrm{C}_s = \begin{bmatrix} \sigma_{C_1} \\ \sigma_{C_2} \\ \vdots \\ \sigma_{C_k} \end{bmatrix},$$

where $\sigma_{C_j}$ is the sensitivity cross-sectional standard deviation of factor "j". Next, we divide, elementwise, the matrix of sensitivities (exposures) by the vector $\mathrm{C_s}$,

$$X_c = X \oslash \mathrm{C_s},$$

where $X_C$ is the sensitivities standardized matrix. To keep units consistent across all entities, we also need to adjust the factors co-var matrix multiplying $\Sigma_f$, elementwise, by

$$\Sigma_{f\mathrm{c}} = \Sigma_f \odot [\mathrm{C_s}\,\mathrm{C_s^t}].$$

The factor returns vector also needs to be adjusted accordingly.

$$R_{f\mathrm{c}} = R_f \odot \mathrm{C}_s.$$

Given the new cross-sectional quantities, then the portfolio security "i" factor return attribution at time "t" reads

$$\mathrm{a}_{i_{c_t}} = X^t_{c_{i_{t-1}}}\, R_{f\,i_{c_t}},$$

and total risk is still given by

$$\sigma_{Tc_i} = \sqrt{\sigma^2_{fc_i} + \sigma^2_{s_i}},$$

where

$$\sigma^2_{fc_i} = X_{c_i}\Sigma_{\mathrm{fc}}\, X^t_{c_i}\,.$$

The extension of the cross-sectional quantities to a portfolio is straightforward. Let us define matrix

$$C_{sp} = \begin{bmatrix} \sigma_{C_1} & \sigma_{C_2} & \cdots & \sigma_{C_k} \\ \sigma_{C_1} & \sigma_{C_2} & \cdots & \sigma_{C_k} \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{C_1} & \sigma_{C_2} & \cdots & \sigma_{C_k} \end{bmatrix}.$$

Matrix $\mathrm{C}_{sp}$ is just vector $\mathrm{C}_{s}^{\mathrm{t}}$ repeated in every row (there are "n" rows, one for each portfolio constituent). Portfolio's sensitivities matrix $\mathrm{X}_{cp}$ is just the elementwise product by $\mathrm{C}_{sp}$

$$X_{cp} = X_p \oslash \mathrm{C}_{\mathrm{sp}}.$$

The cross-sectional risk formulas stay the same by replacing the symbols by their cross-sectional counterparts. The portfolio cross-sectional factor return attribution at time "t" is given by

$$\mathrm{a}_{pc_t} = W^{\mathrm{t}}\, X_{cp_{t-1}}^{t}\, R_{fc_t},$$

and the portfolio's total risk is still given by

$$\sigma_{Tc_p} = \sqrt{\sigma_{fc_p}^2 + \sigma_{s_p}^2},$$

where

$$\sigma_{fc_p}^2 = W^t\, X_{cp}\Sigma_{fc}\, X_{cp}^t\, W \;;\; \sigma_{s_p}^2 = W^t\, \Sigma_s\, W.$$

**Risk Decomposition**

MCTR or *Marginal Contribution To Risk* is a measure used to understand how much a particular asset or risk portfolio component contributes to the overall risk of a portfolio. It is defined as

$$MCTR_i = \frac{Cov(R_i, R_p)}{\sigma_{T_p}},$$

where $R_i$ and $R_p$ are the component "i" and the portfolio returns respectively and $\sigma_{T_p}$ is the portfolio total volatility, or according to our assumptions, risk. By construction it can be easily shown that

$$\sum_{i=0}^{N_p} MCTR_i = \sigma_{T_p},$$

where $N_p$ is the total number of components we are splitting the portfolio over. MCTR is a very convenient way of breaking down portfolio risk as it allows a powerful, yet intuitive and simple, way of identifying and quantifying the sources of risk. Another closely related quantity that shares these convenient properties is

$$Prop\ of\ Risk_i = \frac{MCTR_i}{\sigma_{T_p}},$$

or *Proportion of Risk*. As expected, the sum of all parts of Proportion of Risk always equals 1,

$$\sum_{i=0}^{N_p} Prop\ of\ Risk_i = 1.$$

So, the breakdown of the portfolio risk (MCTR) can be done by:

- Portfolio constituent,
- Macro factor,
- Any combination of the above.

Let us define two auxiliary matrices:

$$\mathrm{A} = \Sigma_f X_p^t W \text{ ; } \mathrm{S} = \Sigma_s \mathrm{W}.$$

Let us identify the portfolio component by “j” and the macro factor by “k”. We also include the risk specific component, “s”, as an extra factor. Then the MCTR reads,

$$\mathrm{MCT}R_{jk} = \frac{W_{(j)}^t \left[ X_{p_{(k \neq s)}} A + S_{(k=s)} \right]}{\sigma_{T_p}},$$

where,

- $W_{(j)}^t$ is the portfolio weights vector with all entries set to 0 except column “j”,
- $X_{p_{(k \neq s)}}$ is the portfolio sensitivities matrix with all entries set to 0 except column “k”, if $k \neq s$ and 0 otherwise,
- $S_{(k=s)}$ is $S$ when $k = s$ and 0 otherwise.

This double decomposition of the MCTR leads to the following summation formula:

$$\sum_{j=0}^{N} \sum_{k=0}^{N_{x+s}} MCTR_{jk} = \sigma_{T_p},$$

where $N$ is the number of portfolio constituents and $N_{x+s}$ is the number of sensitivities (exposures) plus the specific component. If we just want to break down the risk in just one of main components then we do not breakdown the other matrix. Example:

- if we want to split just by “portfolio constituent” ($MCTR_j$), then we replace $X_{p_{(k)}}$ by the full matrix $\mathrm{X}_p$ and $S_{(k=s)}$ by $S$.

- if we want to split just by "macro factor", $(MCTR_k)$, then we replace $W_{(j)}^t$ by $W^t$.

If one would rather like to work with cross-sectional quantities, the above formulae still apply unchanged when the symbols are replaced by their cross-sectional equivalents.

### *(iv) Model Factor & Descriptor Reference*

**US MODEL FACTOR & DESCRIPTOR REFERENCE**

| | factor | descriptor | factor time-series calculation methodology |
|---|---|---|---|
| 1 | **Real Rates** | USD 10Y Real Rate | difference in % |
| 2 | **Metals** | Copper | return in % |
| 3 | **Risk Aversion** | VIX | difference in % |
| 4 | **Inflation** | US 5Y Infl. Expec. | difference in % |
| 5 | **Forward Growth Expectations** | US 5s30s Swap | difference in % |
| 6 | **10Y Yield** | US 10Y Yield | difference in % |
| 7 | **Energy** | WTI | return in % |
| 8 | **Corporate Credit** | US HY | difference in % |
| 9 | **CB Rate Expectations** | FED Rate Expectations | difference in % |
| 10 | **CB QT Expectations** | FED QT Expectations | difference in % |
| 11 | **Economic Growth** | US GDP | difference in % |
| 12 | **DM FX** | USD TWI | return in % |
| 13 | **Market** | S&P500 | return in % |

**EU MODEL FACTOR & DESCRIPTOR REFERENCE**

| | factor | descriptor | factor time-series calculation methodology |
|---|---|---|---|
| 1 | **Corporate Credit** | Itraxx Xover | difference in % |
| 2 | **Metals** | Copper | return in % |
| 3 | **Risk Aversion** | VDAX | difference in % |
| 4 | **Forward Growth Expectations** | Euro 5s30s Swap | difference in % |
| 5 | **10Y Yield** | Euro 10Y Yield | difference in % |
| 6 | **Energy** | WTI | return in % |
| 7 | **CB Rate Expectations** | ECB Rate Expectations | difference in % |
| 8 | **CB QT Expectations** | ECB QT Expectations | difference in % |
| 9 | **Real Rates** | EUR 10Y Real Rate | difference in % |
| 10 | **Inflation** | Euro 5Y Infl. Expec. | difference in % |
| 11 | **Economic Growth** | Euro GDP | difference in % |
| 12 | **DM FX** | EUR TWI | return in % |
| 13 | **Market** | Euro Stoxx 600 | return in % |

**APAC MODEL FACTOR & DESCRIPTOR REFERENCE**

| | factor | descriptor | factor time-series calculation methodology |
|---|---|---|---|
| 1 | **BoJ QT Expectations** | BoJ QT Expectations | difference in % |
| 2 | **BoJ Rate Expectations** | BoJ Rate Expectations | difference in % |
| 3 | **China / EM Stress** | China 5Y CDS, EM CDS | difference in % |
| 4 | **China 10Y Yield** | CNY 10Y Govt. Bond | difference in % |
| 5 | **China Forward Growth Expectations** | China 2s10s Govt. | difference in % |
| 6 | **China Growth** | China GDP | difference in % |
| 7 | **DM FX** | USD TWI | return in % |
| 8 | **EM FX** | USDCNH | return in % |
| 9 | **Energy** | WTI | return in % |
| 10 | **FED QT Expectations** | FED QT Expectations | difference in % |
| 11 | **FED Rate Expectations** | FED Rate Expectations | difference in % |
| 12 | **Japan 10Y Yield** | Japan 10Y Yield | difference in % |
| 13 | **Japan Corporate Credit** | Itraxx Japan | difference in % |
| 14 | **Japan Forward Growth Expectations** | Japan 5s30s Swap | difference in % |
| 15 | **Japan Growth** | Japan GDP | difference in % |
| 16 | **Japan Inflation** | Japan 5Y Infl. Expec. | difference in % |
| 17 | **Japan Real Rates** | JPY 10Y Real Rate | difference in % |
| 18 | **Market** | FTSE Asia Pacific Index | return in % |
| 19 | **Metals** | Copper | return in % |
| 20 | **Risk Aversion** | VIX, VXEEM | difference in % |
| 21 | **US 10Y Yield** | US 10Y Yield | difference in % |
| 22 | **US Corporate Credit** | US HY | difference in % |
| 23 | **US Forward Growth Expectations** | US 5s30s Swap | difference in % |
| 24 | **US Growth** | US GDP | difference in % |
| 25 | **US Inflation** | US 5Y Infl. Expec. | difference in % |
| 26 | **US Real Rates** | USD 10Y Real Rate | difference in % |

GLOBAL MODEL FACTOR & DESCRIPTOR REFERENCE

| | factor | descriptor | factor time-series calculation methodology |
|---|---|---|---|
| 1 | **China Growth** | China GDP | difference in % |
| 2 | **China Stress** | China 5Y CDS | difference in % |
| 3 | **DM FX** | USD TWI | return in % |
| 4 | **ECB QT Expectations** | ECB QT Expectations | difference in % |
| 5 | **ECB Rate Expectations** | ECB Rate Expectations | difference in % |
| 6 | **EM FX** | USDCNH | return in % |
| 7 | **EU 10Y Yield** | Euro 10Y Yield | difference in % |
| 8 | **EU Corporate Credit** | Itraxx Xover | difference in % |
| 9 | **EU Forward Growth Expectations** | Euro 5s30s Swap | difference in % |
| 10 | **EU Growth** | Euro GDP | difference in % |
| 11 | **EU Inflation** | Euro 5Y Infl. Expec. | difference in % |
| 12 | **EU Real Rates** | EUR 10Y Real Rate | difference in % |
| 13 | **Energy** | WTI | return in % |
| 14 | **FED QT Expectations** | FED QT Expectations | difference in % |
| 15 | **FED Rate Expectations** | FED Rate Expectations | difference in % |
| 16 | **Market** | MSCI ACWI | return in % |
| 17 | **Metals** | Copper | return in % |
| 18 | **Risk Aversion** | VIX, VXEEM, VDAX | difference in % |
| 19 | **US 10Y Yield** | US 10Y Yield | difference in % |
| 20 | **US Corporate Credit** | US HY | difference in % |
| 21 | **US Forward Growth Expectations** | US 5s30s Swap | difference in % |
| 22 | **US Growth** | US GDP | difference in % |
| 23 | **US Inflation** | US 5Y Infl. Expec. | difference in % |
| 24 | **US Real Rates** | USD 10Y Real Rate | difference in % |

## Factor Set Glossary

| **Macro Factor** | **Definition** | **Descriptors** |
|---|---|---|
| CB QT Rate Expectations | A swaption (swap option) is the option to enter into an interest rate swap. In exchange for option premium, the buyer gains the right but not the obligation to enter into a specified swap agreement on a specified future date. Here we talk about options on 5yr interest rate swaps 1yr forward in USD, EUR, JPY & GBP. | Fed Quantitative Tightening Expectations |
| CB Rate Expectations | Slope of the relevant money market strip as measured by the spread | Fed Rate Expectations |

| | | |
|---|---|---|
| | between 1y1y forward yield & spot 1y yields. This effectively captures what money markets are discounting in terms of policy rates in the next 12-24 months, i.e. whether the Fed/ECB/BoE/BoJ are hiking or cutting rates & at what speed. | |
| Corporate Credit | An index based on a basket of 100 US single-name high yield Credit Default Swaps (CDS). | US High Yield (US HY) |
| DM FX | An index showing the value of a country's currency in relation to the currencies of a group of countries with which it trades. In the index, each country's currency is given an importance in relation to the amount of trade it does. | USD TWI |
| Economic Growth | US Current Quarter tracking GDP forecast (QoQ %) from Nowcast | US GDP |
| Energy | Front Month Contract Price for West Texas Intermediate Crude Oil | WTI |
| Forward Growth Expectations | The spread between the 5y yield and the 30y yield of the relevant currency | US 5s30s Swap |
| Inflation | 5y inflation expectation for the country as measured by Zero Coupon inflation swaps | US 5yr Inflation Expectations |
| Metals | Front Month Contract Price for Copper | Copper |
| Real Rates | US 10y Generic Nominal Yield minus 10y Expected Inflation | US 10Y Real Rate |
| Risk Aversion | A measure of the implied volatility of S&P 500 index options. Often referred to as the fear index or the | VIX |

| | | |
|---|---|---|
| | fear gauge, it represents one measure of the market's expectation of stock market volatility over the next 30-day period. | |
| 10 Yr Yield | The 10-year Treasury yield is the annualized rate of return you would earn on a 10-year Treasury note issued by the U.S. government if you held the note to maturity. | USD 10Y Yield |
| Market | The S&P 500 is a stock market index tracking the stock performance of 500 of the largest companies listed on stock exchanges in the United States. | SPX Index |

*(v) Bias Stat Definition*

A large, neutral and well-balanced portfolio made of liquid stocks is predicted to have returns that approximately follow a Gaussian distribution. The *Bias Statistic* measures the systematic deviation between the predicted portfolio volatility and realised portfolio volatility as calculated by the macro factor model.

Let us define a new variable:

$$b_t = \frac{R_{p_t}}{\sigma_{p_t}},$$

where $R_{p_t}$ is the portfolio return at time "t" and $\sigma_{p_t}$ is the portfolio *predicted* volatility also at time "t". If the predicted volatility is an accurate prediction of the portfolio volatility, then $b_t$ has an expected standard deviation of 1. We then also define the following statistic

$$\mathrm{B} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(b_t - \overline{b_t}\right)^2},$$

the *Bias Statistic*, where $\overline{b_t}$ is the sample mean.

Statistic $B$ follows a *Chi* distribution and for sufficiently large $T$ can be well approximated by a Gaussian centred on 1 with a standard deviation of $\sqrt{2/T}$ . Therefore, we expect that 95% of the time, $B$ falls inside the interval

$$B \in \left[1 - \sqrt{2/T}, 1 + \sqrt{2/T}\right].$$